Diffusion-based Time Series Imputation and Forecasting with Structured State Space Models

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Abstract

The imputation of missing values represents a significant obstacle for many real-world data analysis pipelines. Here, we focus on time series data and put forward SSSD, an imputation model that relies on two emerging technologies, (conditional) diffusion models as state-of-the-art generative models and structured state space models as internal model architecture, which are particularly suited to capture long-term dependencies in time series data. We demonstrate that SSSD matches or even exceeds state-of-the-art probabilistic imputation and forecasting performance on a broad range of data sets and different missingness scenarios, including the challenging blackout-missing scenarios, where prior approaches failed to provide meaningful results.